

# Geometry of the entropy region - I

Laszlo Csirmaz

Central European University, Budapest

IHP, Paris, February 16, 2016

# Outline

- 1 Information and entropy
- 2 Shannon inequalities
- 3 Case studies
- 4 The “Ringing Bells” distribution
- 5 Common information – the Ingleton inequality

# Entropy

Let  $A$  be a **random variable** taking  $k$  values with probability

$$p_1, p_2, \dots, p_k, \quad (p_1 + p_2 + \dots + p_k = 1).$$

The **entropy** of  $A$  is

$$H(A) \stackrel{\text{def}}{=} \sum_{i=1}^k -p_i \log_2(p_i).$$

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The outcome of  $A$  can be described by  $H(A)$  bits; this is the **information content** of the event  $A$ .

Coin-flipping is 1 bit:  $-\frac{1}{2} \log_2 \frac{1}{2} - \frac{1}{2} \log_2 \frac{1}{2} = 1$ .

## Conditional entropy, mutual information

Let  $A$ ,  $B$  and  $C$  be random variables. The **conditional entropy** of  $A$  given  $B$  is the *average entropy of the conditional distributions*  $A|b$

$$H(A|B) \stackrel{\text{def}}{=} \sum_{b \in B} p_b \cdot H(A|b) = H(AB) - H(B) \geq 0.$$

The **mutual information** of  $A$  and  $B$  is

$$\begin{aligned} I(A, B) &\stackrel{\text{def}}{=} H(A) - H(A|B) = H(B) - H(B|A) \\ &= H(A) + H(B) - H(AB) \geq 0. \end{aligned}$$

The **conditional mutual information** of  $A$  and  $B$  given  $C$  is

$$\begin{aligned} I(A, B|C) &\stackrel{\text{def}}{=} \sum_{c \in C} p_c \cdot I(A|c, B|c) \\ &= H(AC) + H(BC) - H(C) - H(ABC) \geq 0. \end{aligned}$$

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# Before '98

Let  $A$  and  $B$  be *collection* of random variables.

## Shannon inequalities

- ①  $H(A) \geq 0$ ,  $H(\emptyset) = 0$   
– positive,
- ②  $H(B) \geq H(A)$  whenever  $B \supseteq A$   
– monotone,
- ③  $H(A) + H(B) \geq H(A \cup B) + H(A \cap B)$   
– subadditive.

Subadditivity is equivalent to  $I(A, B|C) \geq 0$ .

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**Are there more?**

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# The case of one variable

## Question

What values can take the entropy of a **single** variable?

# The case of one variable

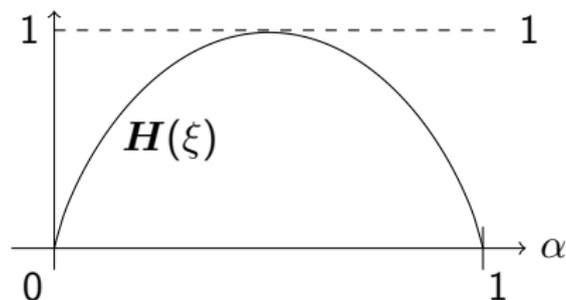
## Question

What values can take the entropy of a **single** variable?

## Answer

Any non-negative real value.

If  $\text{Prob}(\xi = 0) = \alpha$ ,  $\text{Prob}(\xi = 1) = 1 - \alpha$ , then



moreover  $H(\xi\eta) = H(\xi) + H(\eta)$  when  $\xi$  and  $\eta$  are independent.

# The case of two variables

## Question

How does look like the **three** entropies of **two** variables?

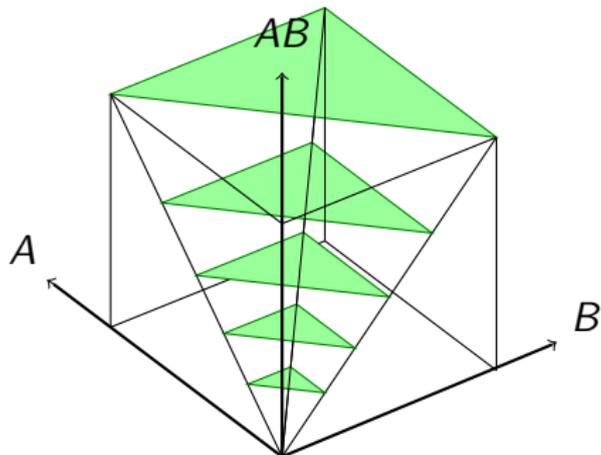
# The case of two variables

## Question

How does look like the **three** entropies of **two** variables?

## Answer

Anything is possible allowed by the Shannon-inequalities.



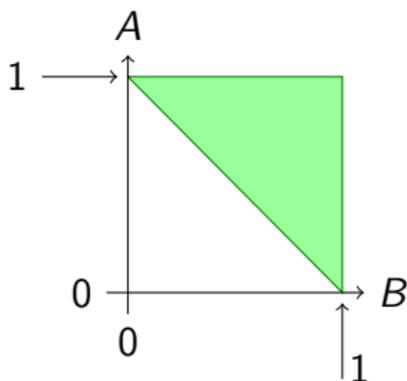
$$0 \leq A \leq AB,$$

$$0 \leq B \leq AB,$$

$$A + B \geq AB.$$

# The case of two variables

Normalize this way:  $AB = 1$



Let  $\xi$ ,  $\eta$ ,  $\zeta$  be independent variables such that

$$H(\xi) = AB - B \geq 0,$$

$$H(\eta) = AB - A \geq 0,$$

$$H(\zeta) = A + B - AB \geq 0.$$

Then

$$H(\xi\zeta) = A, \quad H(\eta\zeta) = B,$$

and

$$H(\xi\zeta, \eta\zeta) = AB.$$

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## Answer

$\mathcal{C}$  is the 7-dimensional cone bounded by the Shannon inequalities. The answer is  $\mathcal{C}$  with some boundary points missing.

## Research & PhD – problem

Describe the **boundary** of the cone  $\mathcal{C}$ .

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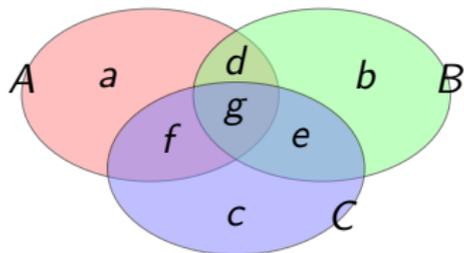
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Describe the **boundary** of the cone  $\mathcal{C}$ .



$a, b, c, d, e, f \geq 0$ ,  $g$  can be  $< 0$ .

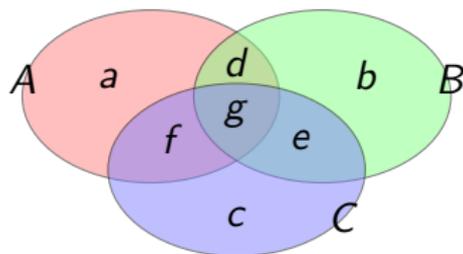
$d + g, e + g, f + g \geq 0$ .

E.g.,  $a = ABC - BC = (A|BC)$ ,

$$d = AC + BC - C - ABC = (A, B|C).$$

# The case of three variables

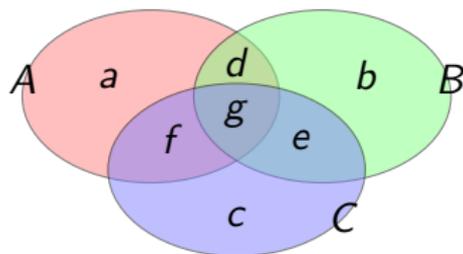
Normalize this way:  $A+B+C=1$ .



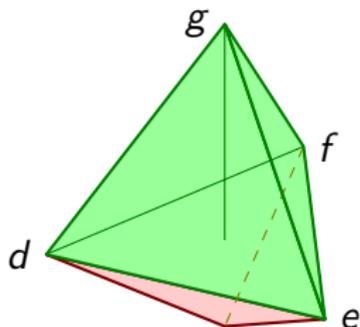
- 1 Take away the private info from A, B, C, i.e., set  $a=b=c=0$ .
- 2 Introduce the **barycentric** coordinates  $(d, e, f, g)$  as  $d + e + f + g = 1$ .
- 3 Visualize the possibilities

# The case of three variables

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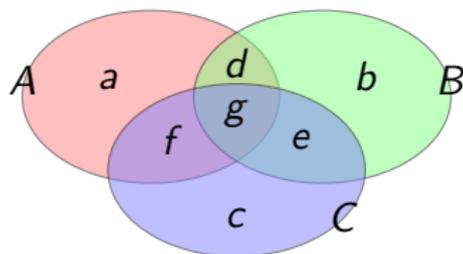
- ① Take away the private info from  $A, B, C$ , i.e., set  $a=b=c=0$ .
- ② Introduce the **barycentric** coordinates  $(d, e, f, g)$  as  $d + e + f + g = 1$ .
- ③ Visualize the possibilities



Every achievable point is a convex linear combination of these **five** extreme distributions – plus **three** accounting for the taken away private info.

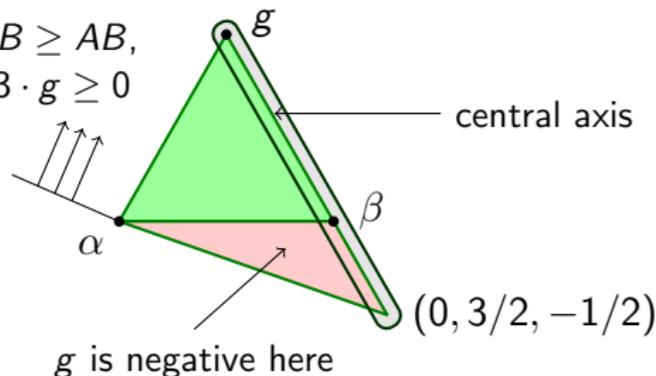
# The case of three variables

Alternate visualization:



- 1 Normalize as before:  $ABC = 1$ .
- 2 Look at the **symmetric core**  
 $\alpha = a + b + c$ ,  $\beta = d + e + f$ .
- 3 Use the barycentric coordinates  $(\alpha, \beta, g)$  as  $\alpha + \beta + g = 1$ .

here  $A + B \geq AB$ ,  
i.e.,  $\beta + 3 \cdot g \geq 0$



# The case of four variables

## Question

How does look like the **fifteen** entropies of **four** variables?

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## Answer

No one knows exactly.

Some partial results:

- its closure is a convex cone, and only boundary points are missing – Zhang and Yeung (1997); Matus (2007)
- It is a **proper** subset of the cone determined by the Shannon inequalities – Zhang and Yeung (1998)
- It has a polyhedral inner core – the **Ingleton base**, which is surrounded by six isomorphic protrusions – Matus and Studeny (1999)
- The closure is **not** polyhedral, thus no finite set of inequalities determines it – Matus (2007)

# The case of five and more variables

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How does look like the  $2^N - 1$  entropies of  $N \geq 5$  random variables?

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## Answer

Much less is known than even for 4 variables.

Lower bound on the share size in perfect secret sharing schemes is an optimization problem on the entropies of  $N$  random variables.

**Conjecture:** the best lower bound is **exponential** in  $N$

**Best known lower bound** is **sublinear**, it's  $N/\log N$ , but exponential lower bound for **linear schemes** (A. Gál )

## Research problem

Improve the log factor in the above estimate.

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# How to define a distribution?

**Simplest method:** list the values and the probabilities.

$\xi_1$	$\xi_2$	$\dots$	$\xi_n$	Prob
$u_1$	$v_1$	$\dots$	$z_1$	$p_1$
$u_2$	$v_1$	$\dots$	$z_1$	$p_2$
$u_1$	$v_2$	$\dots$	$z_1$	$p_3$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$u_j$	$v_k$	$\dots$	$z_\ell$	$p_s$

The probabilities sum to 1:

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**An example:** the *ringing bells*

We have two ropes,  $c$  and  $d$ . When **any of them** is pulled,  $a$  rings, when **both** are pulled,  $b$  rings. Pull each rope independently with  $1/2$  probability.

$a$	$b$	$c$	$d$	Prob
0	0	0	0	$1/4$
1	0	0	1	$1/4$
1	0	1	0	$1/4$
1	1	1	1	$1/4$

# Entropies of the marginal

To get the marginal for a subset of variables: take their columns, merge identical rows, and sum the probabilities.

Original				
$a$	$b$	$c$	$d$	Prob
0	0	0	0	1/4
1	0	0	1	1/4
1	0	1	0	1/4
1	1	1	1	1/4

Marginal on $bc$		
$b$	$c$	Prob
0	0	1/2
0	1	1/4
1	1	1/4

Marginal on $ab$		
$a$	$b$	Prob
0	0	1/4
1	0	1/2
1	1	1/4

The entropy is  $\mathbf{H} = \sum_i -p_i \log_2(p_i)$ . Since  $-(1/4) \log_2(1/4) = 1/2$ ,  $-(1/2) \log_2(1/2) = 1/2$ , thus we have

$$\mathbf{H}(abcd) = 2,$$

$$\mathbf{H}(bc) = 3/2,$$

$$\mathbf{H}(ab) = 3/2.$$

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# Common information

## Definition

For random variables  $\xi$  and  $\eta$  their **common information** is another random variable  $c$  such that

- 1 both  $\xi$  and  $\eta$  determines  $c$ , that is

$$\mathbf{H}(c\xi) = \mathbf{H}(\xi), \quad \text{and} \quad \mathbf{H}(c\eta) = \mathbf{H}(\eta);$$

- 2 any information present both in  $\xi$  and  $\eta$  can be extracted from  $c$  alone:  $\mathbf{I}(\xi, \eta) = \mathbf{H}(c)$ , or, equivalently,  $\mathbf{I}(\xi, \eta | c) = 0$ .

Typically, common information does not need to exist. If it does, it has important consequences on the entropy structure.

# Consequence of common information

## Theorem

Suppose  $a, b, c, d$  are random variables;  $a$  and  $b$  have common information. Then

$$I(a, b) \leq I(a, b | c) + I(a, b | d) + I(c, d).$$

## Proof.

For five random variables  $a, b, c, d, e$  this is a Shannon inequality\*:

$$H(e) \leq 2H(e | a) + 2H(e | b) + I(a, b | c) + I(a, b | d) + I(c, d).$$

If  $e$  is the common information for  $a$  and  $b$ , then  $H(e) = I(a, b)$ ,  $H(e | a) = H(e | b) = 0$ , and we are done.  $\square$

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\*<http://xitip.epfl.ch> or <https://github.com/lcsirmaz/minitip>

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This is the **Ingleton inequality**.

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# The Ingleton score

For the “bells“ distribution

$$H(a) = H(b) = 0.8112\dots$$

$$H(c) = H(d) = 1$$

$$H(ab) = 1.5$$

$$I(a, b) = 0.1225\dots$$

$$I(a, b | c) = I(a, b | d) = 0$$

$a$	$b$	$c$	$d$	Prob
0	0	0	0	1/4
1	0	0	1	1/4
1	0	1	0	1/4
1	1	1	1	1/4

The **Ingleton score** for this distribution is

$$\frac{-I(a, b) + I(a, b|c) + I(a, b|d) + I(c, d)}{H(abcd)} = -0.0612\dots$$

## Research problem

Give better lower and upper bounds on the Ingleton score.

Presently they are  $-0.15789$  and  $-0.09243$ .